Wirtschaftsinformatik 2021 Proceedings

Track 9: Data Science & Business Analytics

Towards a Trust-aware Item Recommendation System on a Graph Autoencoder with Attention Mechanism

Elnaz Meydani
Universität Paderborn

Christoph Düsing
Universität Paderborn

Matthias Trier
Universität Paderborn, Copenhagen Business School

Towards a Trust-aware Item Recommendation System on a Graph Autoencoder with Attention Mechanism

Elnaz Meydani[1], Christoph Düsing[1], Matthias Trier[1,2]

[1] Paderborn University, Department of Management Information Systems, Paderborn, Germany
elnaz.meydani@uni-paderborn.de, cduesing@mail.uni-paderborn.de, trier@uni-paderborn.de

[2] Copenhagen Business School, Department of Digitalization, Frederiksberg, Denmark
mt.digi@cbs.dk

Abstract. Recommender Systems provide users with recommendations for potential items of interest in applications like e-commerce and social media. User information such as past item ratings and personal data can be considered as inputs of these systems. In this study, we aim to utilize a trust-graph-based Neural Network in the recommendation process. The proposed method tries to increase the performance of graph-based RSs by considering the inferred level of trust and its evolution. These recommendations will not only be based on the user information itself but will be fueled by information about associates in the network. To improve the system performance, we develop an attention mechanism to infer a level of trust for each connection in the network. As users are likely to be influenced more by those whom they trust the most, our method might lead to more personalized recommendations, which is likely to increase the user experience and satisfaction.

Keywords: Recommender Systems, Trust-aware Recommendations, Autoencoders, Attention mechanism

1 Introduction

Information overload is one of the major problems in many online applications such as e-commerce and social networking websites. Recommender Systems (RSs) have become a promising tool to handle this problem by generating individualized recommendations [1]. Collaborative Filtering (CF) is one the most popular algorithms in RSs, which predicts a user's interest in an item through mining the patterns of the existing rating information of other similar users/items [2]. The main idea of CF is to predict future ratings or purchases based upon collected user-item interactions, represented in a user-item interaction matrix. The approach additionally considers the preferences of associated users modeled as a user-user-connection graph. The user-user connection is usually being defined as friendship or followership between two users, both implying some form of trust between them [3]. Following the basic data structure, RSs based on Graph Neural Networks (GNNs) have been developed which have shown promising results in applications such as e-commerce and social media [4–6].

The theory of social homophily describes that similarity breeds connection. Accordingly, the people's networks of those whom they trust are more homogenous concerning many sociodemographic, behavioral, and interpersonal characteristics,

16th International Conference on Wirtschaftsinformatik,
March 2021, Essen, Germany

including attitude towards certain commodities [7]. Consequently, from the observation of trust, possible interests can be derived from associated users in a trust graph [7]. Following this idea, some studies have utilized this concept to not only consider the explicit trust observed in a network but also implicit trust and the dynamics of it to recommend a user possible items of interest [1]. The main idea is to employ trust propagation to predict the level of trust in unknown users [8]. These trust metrics, emerging recently as a powerful technique, can then be utilized to personalize the user experience by emphasizing content entered by trusted users and hiding content provided by unreliable ones [8]. In the context of social media, however, this level of trust is rarely expressed directly, and thus has to be inferred from interactions and other side-information for each pair of related users.

In previous researches, both trust-aware and GNN-based RSs were found to perform well [1], [2], [4–6]. In our proposed approach, we aim to jointly utilize the two aforementioned concepts, GNNs, and level of trust, within a novel recommendation model. This GNN-based RS will capture the preferences of each user in a network as well as these users' interrelations to generate item recommendations. In particular, we will train a Deep sociodemographic GNN to not only accomplish such recommendations but also to infer the level of trust for each user to its direct and n-level neighbors. To accomplish the latter, we extend our GNN by an attention mechanism, as it was proposed in [1]. Attention mechanism in GNNs is originally introduced in [6] and allows to learn the contribution of each user to the recommendation for others, whereby this contribution indicates the inferred trust.

The proposed method tries to increase the performance of graph-based RSs by considering the inferred level of trust and its evolution. As users are likely to be influenced by those whom they trust the most, including the level of trust in our method might lead to more accurate recommendations. Thus, the contribution of our work is to generate more personalized recommendations using our model that aggregates the information from the most trusted users in the trust network. This is likely to increase user loyalty, satisfaction, and experience in online applications and respectively increase provider sales.

2 Related Literature

2.1 Trust-based Recommendations

The consideration of trust as side information in RSs, also referred to as Trust-aware RSs (TARS), has been investigated in several studies [1], [9], [10]. Typically, the trust network has been created from real-world observations. The concept of trust could either be revealed explicitly by the users or be inferred implicitly from their friendship or followership relations [2]. Both methods collect information about the direct associates of each user. The resulting network consists of nodes representing users and edges representing the trust between them [1]. In a weighted trust network, these edges are also weighted by the observed level of trust [1]. Within a trust-network, the level of trust between non-direct neighbors can then be inferred concerning the distance between users and the individual level of trust of each relation along the shortest path [10]. Both observed and implied levels of trust are then utilized to weight the effect of each user in a network on the recommendation for a specific user of interest. The more the target user trusts other users in his/her network, the more his/her recommendations are affected by other users' preferences [1]. The TARS approach has been shown to predict more accurate ratings and hence more individualized recommendations than traditional RSs by considering the trust factor [1].

2.2 Attention Mechanism

TARS relies on observations of trust within a network [1], [9], [10]. However, users trust others to varying degrees, even though this might not be included in the information about a network. To address this problem, Graph Attention Networks (GATs) can be used to learn the weights of each connection between users in a network [11]. GATs implement an attention mechanism, which allows learning a weight per edge [11]. These weighted connections characterize how strong the recommendations for a user u_i depends on the information received from the associated user u_j [11]. According to the theory of social homophily [7] and its bonding preference for similar actors, it can be logically derived that a target user is being influenced more by the users, whom they trust the most. Hence, the learned weight for each edge serves as an indicator for the level of trust between the related users [11].

2.3 Graph-based Autoencoder

The application of autoencoders, an unsupervised deep learning algorithm, in RSs has shown promising results in recent studies [12], [13]. Due to their good performance, they have been jointly applied with GNNs [4]. The framework proposed in [4] is capable of recommending items to a user based on his/her past interactions with items as well as his/her connections to other users within a network [4]. Thus, direct neighbors affect the recommendations more than other users. Van Berg et al. [4] did not consider weak or strong ties between users and assign each user the same relevance for the recommendation. They propose the application of attention mechanisms in future research [4]. While Feng et al. in [14] followed the idea of integrating attention mechanisms into GNNs, the combination of trust-graph-based autoencoders with attention mechanisms to infer a level of trust between each user remains a gap in the existing research. Although the performance of both approaches shows promising results, applying a combination of both methods might outperform their isolated application. Recent research proved that such all-in-one approaches significantly improve the quality of results compared with single applications one after another [4].

3 Methodology

In this study, we adopt the Design Science Research Methodology (DSRM) process model proposed by Peffers et al. (2007) and develop a model to improve the performance of RSs, aiming at generating more personalized recommendations. The DSRM process model consists of six main activities [15]. The first two activities are the identification of a problem and motivation, and the objectives for a solution, which are illustrated in the introduction part of this paper. In this sub-section, we explain the details of the design and development of our proposed model. In the "Experiments" sub-section, we provide details about the experiments and the evaluation of our proposed model. The proposed model can be divided into three main phases: trust-graph creation phase, training phase, and recommendation phase.

3.1 Trust-graph Creation Phase

The Epinions dataset consists of information about the rating users made on items on one hand, and information about which users trust others on the other hand. The trust is a binary value in this dataset and does not include a differentiated level of trust [16]. The trust-graph is created by combining both types of information. The nodes and their relations are taken from the source of user-user trust information. After that, each node obtains features based on their past item ratings. These features are composed of information about each existing item and if/ how a user rated them. Based on this graph, the GNN Autoencoder will be trained in the next step.

3.2 Training Phase

In this phase, we train the GNN autoencoder to combine neighboring information with the observed ratings of each user and to predict ratings for such items, where no direct ratings were observed so far. During the process and due to the nature of GNNs, information about each node will be passed along the connections in the network, which allows learning the recommendations based upon the information of each n-level neighbors in the network, where, n arises from the number of layers in the network and will be selected concerning the best results. The attention mechanism is also included in the architecture of the underlying model and will allow learning a level of trust for each pair of directly associated users. For users who are not directly related, the overall procedure finds an implicit level of trust between them. Figure 1 shows the formerly unweighted trust-network (a), received from the creation phase. With the help of the attention mechanism, these edges could now be weighted (b). The level of trust will be used to weight the influence on the recommendations.

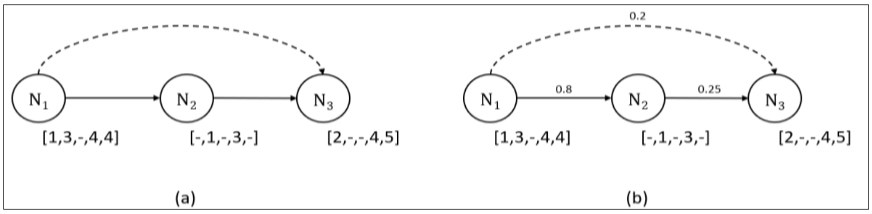

Figure 1. Trust-network including rating information for each user. (a) is created directly from the data and (b) results after the application of the attention mechanism.

3.3 Recommendation Phase

The trained model outputs the expected ratings each user has for each item, but with a special level of trust learned from the training phase. These predicted ratings will be compared with the truly observed ratings. At each point, where the prediction gives a good rating for an item, for which a user has not rated yet, a recommendation will be accomplished. By doing so, the model is of special interest when users with very few or no ratings at all are considered. Even for such users, a recommendation can be attained.

4 Experiments

Within the limited scope of this short paper, we provide a summary of the details of the experiments and evaluation. To measure the performance of our proposed framework, we will conduct experiments on two datasets and compare the results of our model with the graph-based state-of-the-art models. We choose GCMC+SN [4], GraphRec [17], and DANSER [18] models as evaluation baselines in our study. These experiments will be applied to two public known benchmark datasets, namely the Epinions and Ciao datasets[1]. Both datasets consist of user-item rating pairs with rating scores from 1 to 5, as well as the directed trust information between users. Trust is a binary value in both datasets and does not include a differentiated level of trust.

To evaluate the quality of our proposed recommendation algorithm, we adopt two popular metrics, namely, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Following the work of van den Berg et al. (2017), we use these evaluation metrics to evaluate the predictive accuracy of our proposed model and to compare our model with state-of-the-art baseline models. A smaller value of MAE and RMSE means less error score for the predicted item ratings and consequently a better performance of the model. The first results on both datasets show the superior performance of our proposed model. We believe that combining trust information into the recommendation process mitigates the cold-start users/items and data sparsity problem. To investigate the performance of our proposed model for cold-start users, we will test the model in the presence of users with only a few ratings (cold-start users) and monitor the MAE/RSME.

5 Outlook

In this paper, we present a novel approach to improve graph-based recommendations by including information obtained from a user-user trust-network to increase the overall performance and especially the quality of recommendations for users new to the network, which so far remains a challenge even for state-of-the-art RSs. This method is likely to increase the satisfaction of the users and the sales of providers. In the next step, we will continue to increase the performance of our model with special respect to cold-start users and items. Moreover, we will provide insights into how a level of trust can be inferred, how this trust evolves, and how it improves the quality of recommendations. Further evaluation of real-world applications will follow in the future.

[1] https://www.cse.msu.edu/~tangjili/datasetcode/truststudy.htm

References

1. Li, J., Yang, R., Jiang, L.: DTCMF: Dynamic trust-based context-aware matrix factorization for collaborative filtering. In: 2016 IEEE Information Technology, Networking, Electronic and Automation Control Conference, pp. 914–919 (2016)
2. Li, J., Sun, C., Lv, J.: TCMF: trust-based context-aware matrix factorization for collaborative filtering. In: 2014 IEEE 26th international conference on tools with artificial intelligence, pp. 815–821 (2014)
3. Massa, P., Avesani, P.: Trust-aware recommender systems. (2007)
4. van den Berg, R., Kipf, T.N., Welling, M.: Graph convolutional matrix completion. arXiv preprint arXiv:1706.02263 (2017)
5. Pande, A., Ni, K., Kini, V.: SWAG: Item Recommendations using Convolutions on Weighted Graphs. In: 2019 IEEE International Conference on Big Data (Big Data), pp. 2903–2912 (2019)
6. Guo, Z., Wang, H.: A Deep Graph Neural Network-based Mechanism for Social Recommendations. IEEE Transactions on Industrial Informatics (2020)
7. McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a feather: Homophily in social networks. Annual review of sociology 27, 415–444 (2001)
8. Avesani, P., Massa, P., Tiella, R.: A trust-enhanced recommender system application: Moleskiing. In: Proceedings of the 2005 ACM symposium on Applied computing, pp. 1589–1593 (2005)
9. Golbeck, J.A.: Computing and applying trust in web-based social networks (2005)
10. Alahmadi, D.H., Zeng, X.-J.: Twitter-based recommender system to address cold-start: A genetic algorithm based trust modelling and probabilistic sentiment analysis. . In: 2015 IEEE 27th International Conference on Tools with Artificial Intelligence (ICTAI), pp. 1045–1052 (2015)
11. Veličković, P., Cucurull, G., Casanova, A., Romero, A., Lio, P., Bengio, Y.: Graph attention networks. arXiv preprint arXiv:1710.10903 (2017)
12. Li, X., She, J.: Collaborative variational autoencoder for recommender systems. In: Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining, pp. 305–314 (2017)
13. Liang, D., Krishnan, R.G., Hoffman, M.D., Jebara, T.: Variational autoencoders for collaborative filtering. In: Proceedings of the 2018 World Wide Web Conference, pp. 689–698 (2018)
14. Feng, C., Liu, Z., Lin, S., Quek, T.Q.S.: Attention-based graph convolutional network for recommendation system. In: ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 7560–7564 (2019)
15. Peffers, K., Tuunanen, T., Rothenberger, M.A., Chatterjee, S.: A design science research methodology for information systems research. Journal of management information systems 24, 45–77 (2007)
16. Zhong, H., Zhang, S., Wang, Y., Shu, Y.: Study on directed trust graph based recommendation for e-commerce system. International journal of Computers communications & control 9, 510–523 (2014)
17. Fan, W., Ma, Y., Li, Q., He, Y., Zhao, E., Tang, J., Yin, D.: Graph neural networks for social recommendation. In: The World Wide Web Conference, pp. 417–426 (2019)

18. Wu, Q., Zhang, H., Gao, X., He, P., Weng, P., Gao, H., Chen, G.: Dual graph attention networks for deep latent representation of multifaceted social effects in recommender systems. In: The World Wide Web Conference, pp. 2091–2102 (2019)